A New Shadow Tracking Method to Locate the Moving Target in SAR Imagery Based on KCF

Zhenhua Xu, Yun Zhang(✉), Hongbo Li, Huilin Mu, and Yuan Zhuang

Harbin Institute of Technology, Harbin 150000, China
zhangyunhit@hit.edu.cn

Abstract. Shadow detection and tracking (SDT) is the effective method to locate moving targets, which always be shifted or smeared outside the scene, in different images sequence by Synthetic Aperture Radar (SAR). In this process, the detection of shadow is obtained on the first frame image, and the Kernelized Correlation Filter is used to track target among the following SAR images, using the changes between the image sequence. By the experiments and performance analysis, the validity of the proposed algorithm can be demonstrated.

Keywords: ViSAR · Shadow · Moving target detection · KCF

1 Introduction

SAR has been wildly used for land observation, mapping, disaster monitoring, and so on. Conventional SAR is able to obtain high resolution ratio images of static environment or objects, and it can realize moving targets' detection and location by Ground Moving Target Indication. However, because of long integration time, the frame rate of conventional SAR imaging is far lower than the need for target tracking. this problem, a new SAR system, Video-SAR or ViSAR is proposed by Well in 2003 [1], which can obtain image sequence of target area and reproduce area information in a movie-like form. ViSAR meet the more needs for target tracking and monitoring than conventional SAR. Moving target's detection and tracking by SAR are still in preliminary stage of development. Such as Dungan's research about wide-angle's influence on car targets detection [2], DRDC (Defense Research and Development Canada) use BP algorithm for detection and Yamaoka's low complexity method to generate Radar video [3]. In this article, it proposes a new kind of processing method for target detection and tracking on ViSAR. It improves algorithm to detect target based on PCNN and track target by KCF (Kernelized Correlation Filter).

2 Moving Target in the Circular Video-SAR

In circular SAR system, the imageries are obtained as a serial frame, stationary targets show different reflection by different incident, and moving targets show the different location and focusing. To keep tracking a target or monitoring a interested area, the

Q. Liang et al. (Eds.): CSPS 2017, LNEE 463, pp. 2661–2669, 2019.
https://doi.org/10.1007/978-981-10-6571-2_322

processing of video on circular SAR raw data can improve the change detection on imagery sequence. Circular ViSAR can obtain scattering characters from all the directions which leads to high detection precision, expanding wave-number domain effective bandwidth, even get the 3D information or 4D information of targets. The geometry of Circular Video-SAR is shown in Fig. 1.

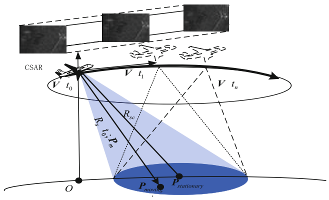
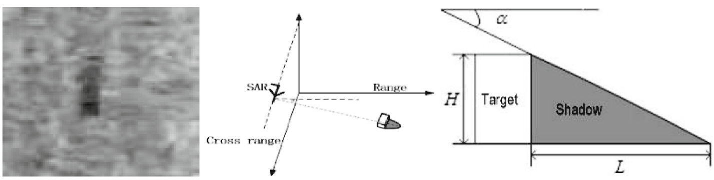


Fig. 1. The geometry of Circular Video-SAR

In SAR image, moving targets is a hard to detected and located which Doppler energy may be shifted or smeared outside the scene, so tracking target is even difficult. However, the shadow of the target is created by the incident angle of radar look light, and the height of target from illuminating. So, In SAR imagery, although the echo of moving target is changed too fast to detect, track or identify, but target shadow can provide insight, which depend on its physical dimension. The shadow is moving followed the mobility of a target, with the platform and radar imaging parameters. This paper obtains the accurate location of target by its shadows tracking. The following Fig. 2 shows how shadow is generated.



(a)Moving car's shadow (b)Sketch in 3D (c) Sketch in 2D

Fig. 2. The geometry of target shadow

Because the plane is flying in a circle, so the image sequence obtained rotates too. In order to use optical tracking method to realize target tracking, registration needs to be done before optical tracking.

3 Target Tracking Method Based on KCF

KCF means Kernelized Correlation Filter, which is proposed by Henriques et al. in 2014. This is a very effective target tracking algorithm with high speed used to track interested target in optical image [4]. In this section, a method of target's shadow tracking by KCF is introduced to detect the moving target in SAR image.

3.1 Mathematical Model of KCF

Current mainstream tracking methods base on *tracking-by-detection*, and the nature of *tracking-by-detection* is a process solving a regression problem. The main step in the regression is solving a minimizer w as Eq. 2 shown. The calculation process is complicated because of large amount of data. To solve this problem, KCF puts forward a new method by creating circulant sample matrices and do the calculation work in Fourier domain. Because of the fact that convolution of two patches is equivalent to an element-wise product in the Fourier domain, KCF considerably reduces computation complexity.

3.1.1 Linear Regression

First, we focus on linear regression. In the original, training samples is a process to solve a Ridge Regression problem, and the goal is to find a function $f(z)=X^T z$ that minimizes the square error over samples x_i and regression targets y_i

$$\min_{w} \sum (f(x_i) - y_i)^2 + \lambda \|w^2\| \tag{1}$$

The λ is used to control overfitting. This regression has a minimizer form as

$$w = \left(X^H X + \lambda I\right)^{-1} X^H y \tag{2}$$

where the matrix X has one sample per row x_i, and each y_i is a regression target. Here, X^H is the Hermitian transpose, i.e., $X^H = (X^*)^T$.

Considering an n × 1 vector x as a patch with the target of interest, we refer to it as basic sample. Then we have the data circulant matrix $X = C(x)$ by cyclic shifts as Fig. 3 shows.

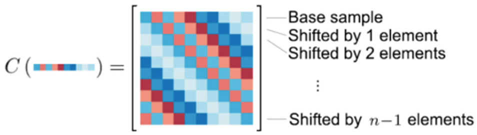


Fig. 3. Circulant matrix: the first row is the initial vector and every other rows is cyclic shifts of it.

Circulant matrices have a very useful property: all circulant matrices are made diagonal by the DFT regardless of the base sample vector. What's more amazing is that diagonal matrices are also very appealing because all operations can be done element-wise on their diagonal elements. It is this property that makes it possible to reduce complexity considerably. This can be expressed as

$$X = F\, diag(\hat{x})\, F^H \tag{3}$$

where F is known as the DFT matrix and it's a constant unitary matrix that does not depend on x. $\widehat{x}$ represent DFT of the generating vector, $\widehat{x} = DFT(x)$. X is the generated circulant matrix.

After a series of processing we have

$$\widehat{w} = \frac{\widehat{x}^* \cdot *\widehat{y}}{\widehat{x}^* \cdot *\widehat{x} + \lambda} \tag{4}$$

where $\cdot *$ means element-wise product. Here we have the result $\widehat{w}$ representing minimizer w's DFT, so we can easily have the result minimizer w with IDFT.

3.1.2 Non-linear Regression

Non-linear regression is developed from linear regression. It has a pretty attractive quality: the optimization problem is still linear. So, the input of a linear problem is mapped to a non-linear problem feature-space $\varphi(x)$ with the kernel trick. Then, the solution w as a linear samples combination is

$$w = \sum\nolimits_i \alpha_i \varphi(x_i) \tag{5}$$

It's variable α that is under the optimization instead of w from the equation, which is the non-linear regression.

The algorithm can be expressed in terms of dot-products $\varphi^T(x)\varphi(x') = \kappa(x, x')$, computed by the kernel function κ (e.g., Gaussian or Polynomial). The dot-products usually stored in a $n \times n$ kernel matrix K whose elements are

$$\mathrm{K}_{i,j} = \kappa(x_i, x_j) \tag{6}$$

then we have kernelized version of Ridge Regression [5]

$$\alpha = (\mathrm{K} + \lambda I)^{-1} y \tag{7}$$

Knowing variables α, we can easily derive classification function

$$f(z) = X^T z = \sum\nolimits_i^n \alpha_i \kappa(z, x_i) \tag{8}$$

then we can easily classify new input samples with the function $f(z)$. So the core step now is deriving variables α. The process are shown in the following part.

Let's define κ^{xx} as the first row of K, it can be proved that K is a circular matrix $\mathrm{K} = \mathrm{C}(\kappa^{xx})$ [5]. Then the kernel regression solution is the training result

$$\widehat{\alpha} = \frac{\widehat{y}}{\widehat{\kappa^{xx}} + \lambda} \tag{9}$$

After knowing $\widehat{\alpha}$ we can derive $\widehat{f(z)}$. So have the regression result, which is also the detection result

$$\widehat{f(z)} = \widehat{\kappa^{xx}} \cdot * \widehat{\alpha} \tag{10}$$

From the result of non-linear regression, we can easily find out that kernel $\kappa(x, x')$ is very important, so the choice of kernel will considerably affect the tracking effect. The most important property the kernel must have is that the kernel value should be unchanged by unitary transformation, such as DFT. *Gaussian Kernel* and *Polynomial Kernel* are proved to be able to be used in KCF.

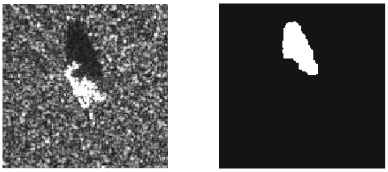
3.2 Target's Shadow Detection in SAR Image

The shadow of target is able to well represent target's feature, extracting target's shadow's information is especially useful in moving target tracking.

In this section, the extraction of shadow information in SAR image is improved PCNN. The image is full of small disturbance points after extraction, and the post processing method is mathematical morphology processing method. Because morphology operator's structure element is always pretty big, most of the edge information of the shadow will be lost. First, LEE filter is used to reduce speckle noise, then we detect target's shadow by using improved PCNN mentioned before. After that, there will be a lot of small disturbance points caused by speckle noise in the image, so we need to delete some parts whose area of connected pixels is less than 50 in order to remove those disturbance points. In addition, the image needs to be smoothed to remove the burr of the shadow areas.

3.2.1 Extraction of Shadow's Geometric Feature

According to geometric extraction algorithms mentioned above, the main geometric information of shadow includes area, perimeter and axial ratio. Results are as follow in Fig. 4.



(a)Original SAR image (b)Image of extracted shadow area

Fig. 4. Geometric feature of T72 tank

3.2.2 Extraction of Shadow's Zernike Edge Feature

Based on Zernike edge algorithm we extract the information of shadow's edge. Because Zernike edge algorithm bases on subpixel edge detection theory, it can extract edge information more accurately. The results are shown in the Fig. 5.

(a)Original SAR image (b) shadow area (c)Extracted edge area

Fig. 5. Extraction results of T72 tank using Zernike edge algorithm

3.3 Moving Target Tracking Based on KCF

In this section, a detailed introduction of our tracking method based on KCF + HOG is given. KCF requires the accurate location of interested target and the size of the tracking template, which is a rectangle, in the first frame. Then KCF will track the target in the templates based on the algorithm mentioned above. The target's location can be obtained from the detection method mentioned in Sect. 3.2 The framework of proposed tracking method is shown in Fig. 6.

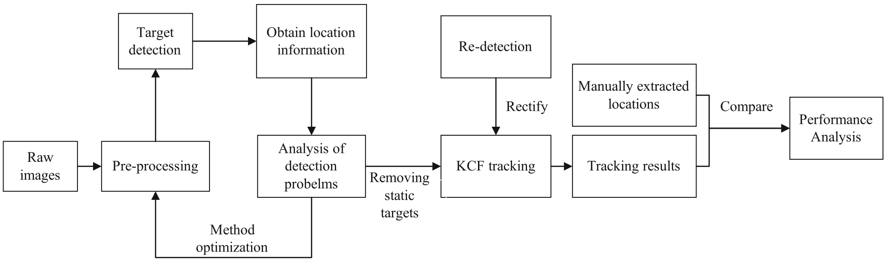


Fig. 6. Schematic of the proposed tracking method

3.3.1 Image Pre-processing

In circular ViSAR, the plane is flying in a circle, so the image sequence obtained rotates. In order to use KCF tracking method to realize target tracking, image registration needs to be done before tracking. SAR image tend to have much lower quality, usually with higher noise, disturbance and more blurred boundaries. So after registration a series of processing needs to be done to improve image quality, such as removing the speckle noise by using LEE filter, enhancing local details with histogram equalization and so on.

3.3.2 Undesired Detection Problems and Relative Solutions

KCF needs shadow's location obtained from detection in the first frame, and obviously, the detection part can't be perfect. Here we list two kind of undesired situations that may happen during the detection.

Moving target's shadow is skipped. When the edge feature (using HOG operator) of target's shadow is obscure, it may be skipped by KCF. When this happens, optimization of pre-processing method and the detection algorithm is needed.

Static target's shadow is detected. Because the strong similarity between moving target's shadow and static target's shadow, this situation happens a lot. But static shadow's tracking template won't move, so we can easily solve this problem by deleting templates which don't move for longer than a certain period.

3.3.3 Tracking Method

After getting the location information of target's shadow, we can keep tracking the shadow by using KCF. But in traditional tracking method, if the tracking template loses the target it will lose it forever, which means even one frame's mistake can lead to failure of one target's tracking.

To avoid it happening, we rectify the tracking process by re-detecting the target every certain period. The error accumulates with the tracking time increases, periodically detecting the target for another time can eliminate errors. The target re-detection is limited in the surrounding area of the target in the last frame. The length of the period can be adjusted based on specific conditions and the value should be well selected. If the period is too short, the speed of the tracking will be severely affected because target detection is much slower than KCF; if the period is too long, the accumulated error can be pretty large and it's bad for the following re-detection.

3.3.4 Calculating Speed and Accuracy

When the tacking finishes, we need to calculate the frame rate and accuracy to evaluate real-time and accuracy of the method in order to make the tracking method meets our needs.

Frame rate can be easily obtained by calculating the amount of outcome images per second. For accuracy calculation, we need to record the location of target in every frame and then compare these manually extracted data with tracking result, then we can evaluate the accuracy by the comparison.

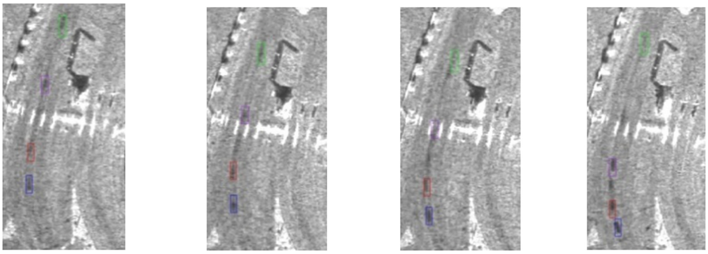
4 Experiments and Analysis

In this part, we mainly show the simulation results and relative analysis. Some results are still remained to be optimized in the future so better results can be expected. The tracking result is a series of images with interested targets tracked by the templates, and the tracking process can reach almost 30 FPS with 4 targets tracked at the same time on a normal laptop. Results are shown in Fig. 7.

Because of limited time, we have not added re-detection part into the tracking simulation and that's why the target at the top of the image is lost at about 20th frame. This problem can be easily solved by re-detection in future research.

To obtain targets' speed and moving routes, we record the tracking templates' location in every frame. Also, the records of tracking templates can be very helpful in our further method optimization, shown as Fig. 8 shows.

All the processing is done on normal laptop, so the speed can increase a lot with the optimization of the method and use of GPU in the future (Table 1).



(a)The first frame (b) The 10th frame (c)The 20th frame (d) The 40th frame

Fig. 7. Frames extracted from tracking results. Three targets are well tracked but the top target (green template) is lost at about 20th frame (Color figure online)

Table 1. Tracking FPS results

Target numbers	FPS
One target	52.7741
Two targets	38.6000
Three targets	30.6361
Four targets	27.0827

Another important index is tracking accuracy which is shown in Fig. 9. The figure shows the accuracy of the target tracked by blue template (the bottom one in the image) in Fig. 7. And other targets' accuracy curves are just like Fig. 9 except the target tracked by green template (the top one in the image).

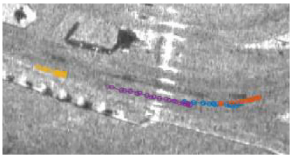


Fig. 8. The routes of tracking templates

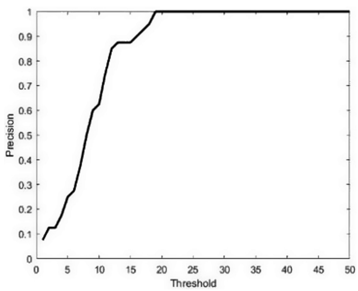


Fig. 9. Accuracy curve of the target tracked by blue template (the bottom one in the image) (Color figure online)

5 Conclusion

In this article, a novel shadow tracking method by KCF is improved to SAR target tracking, with Re-detection processing. The proposed tracking method can effectively track target in SAR image with high speed and accuracy. In later work, we will optimize the whole framework and bring in the concept "Forecast" to reduce complexity with the same high accuracy.

Acknowledgement. This work was supported by the National Natural Science Foundation of China 61201304 and 61201308, It also thanks for the Aerospace Innovation Foundation.

References

1. Wells, L., Sorensen, K., Doerry, A., et al.: Developments in SAR and IFSAR systems and technologies at sandia national laboratories. In: Aerospace Conference (2003)
2. Dungan, K.E.: Vehicle detection in wide-angle SAR. In: SPIE Defense+Security, pp. 98430H–98430H-6. International Society for Optics and Photonics (2016)
3. Yamaoka, T., Suwa, K., Hara, T., et al.: Radar video generated from synthetic aperture radar image. In: 2016 IEEE International on Geoscience and Remote Sensing Symposium (IGARSS), pp. 6509–6512. IEEE (2016)
4. Henriques, J.F., Caseiro, R., Martins, P., Batista, J.: High-speed tracking with kernelized correlation filters. In: TPAMI, pp. 3–5 (2014)
5. Rifkin, R., Yeo, G., Poggio, T.: Regularized least-squares classification. Nato Sci. Ser. Sub Ser. III Comput. Syst. Sci. **190**, 131–154 (2003)